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End-to-End Energy System Modeling with Large Language Model Agents and Workflow Automation

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Abstract

This paper introduces X-AI, a domain-aligned, agent-orchestrated, fully integrated modeling environment constructed to advance digital modernization in the energy industry. X-AI weaves sophisticated Machine Learning (ML) and Deep Learning (DL) functions into a process-driven setting, empowering energy practitioners to build and launch predictive solutions without requiring previous AI know-how. A central breakthrough lies in the incorporation of Dragon Dawn (D2), an intelligent assistant fueled by Large Language Models (LLMs) and logic-based agent mechanisms. D2 deciphers commands expressed in everyday language, fetches pertinent domain material, arranges modeling sequences, and steers layered optimization cycles, consequently diminishing technical obstacles and mental strain for operators. To measure platform usability quantitatively, an original measure dubbed the Cognitive-Operation Efficiency Ratio (COER) is proposed, capturing both how efficiently tasks are completed and how much cognitive exertion is involved. Test outcomes indicate that D2 substantially lifts modeling throughput, yielding greater than an eightfold rise in COER. A genuine case examination concerning inflow prediction across cascading hydropower installations substantiates the platform's potential. Through juxtaposing an LSTM architecture against an XGBoost variant guided by D2, the work reveals how the assistant promotes cyclical reasoning, variable refinement, and parameter optimization. These results solidify X-AI as a workable, scalable AI instrument for fast-tracking informed decision-making in the energy sector.

Keywords Large language models, Agent systems, No-code modeling, Hydropower forecasting, Usability evaluation, Intelligent platforms

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Introduction

Artificial Intelligence (AI) is reconfiguring industrial landscapes through greater automation, smarter decision-making processes, and forward-looking analytics [1]. The energy domain, distinguished by intricate networks, mission-critical assets, and mounting ecological imperatives, presents vast opportunities for AI-powered evolution. AI approaches can materially boost operational effectiveness [2], prognostic reliability [3], and resource coordination [4] across electricity generation, storage, and grid management.

Notwithstanding the wealth of information held by contemporary energy firms, the tangible exploitation of AI remains narrow. This gap often stems from siloed data systems and a shortage of versatile, sector-customized AI frameworks [5]. AI draws together numerous disciplines—mathematics, computer science, Machine Learning (ML), data wrangling, domain-tuned algorithm design, and rollout. Producing skilled AI personnel demands extensive effort and cross-field

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preparation. Concurrently, digitalisation ranks among the foremost catalysts reshaping the power business [6]. To accelerate this transition, there is an acute need for smart, no-code environments that let field specialists independently create and steward AI solutions. No-code denotes a building philosophy wherein users assemble applications or procedures via visual dashboards and ready-to-use modules, circumventing heavy programming. This paradigm radically shrinks the proficiency barrier for non-coders, permitting domain experts to craft and maintain AI systems with negligible hand-coding. Within energy-focused AI, where many engineers lack structured software training, no-code surfaces prove exceptionally valuable for accelerating adoption and compressing development cycles.

Beyond generic hurdles to AI assimilation, the energy business surfaces sector-unique impediments that constrain real-world rollout of intelligent tools. To begin with, energy data exhibits deep heterogeneity, spanning tabular records (e.g., sensor streams, Supervisory Control and Data Acquisition (SCADA) archives), freeform documents (e.g., water resource memos, standard operating protocols), and geographic-temporal fluctuations. Secondly, analytical undertakings call for niche disciplinary insight—such as water cycle mechanics, electricity dispatch logic, and seasonal runoff behavior—which off-the-shelf AI toolkits seldom encode effectively. Thirdly, engineers predominantly hold backgrounds in mechanical, civil, or electrical branches, which can obstruct the design and sustainment of ML/DL pipelines. Lastly, the field must meet elevated benchmarks for safety, interpretability, and statutory compliance, imposing stricter expectations for system transparency and ease of use. These particular frictions underline the demand for domain-attuned AI environments that go beyond merely lowering technological entry points and actively embed power-sector knowledge into workflows and user experiences.

A range of recent environments has emerged, including BONSEYES [7] for embedded AI crafting, iSee [8] for interpretable agent-grounded reasoning, and DADOS [9] for cloud-resident optimization. While competent in circumscribed scenarios, these systems generally preserve an algorithm-first posture and fall short on intuitive, engaging interfaces, thereby curbing uptake among domain practitioners. As AI penetration widens across markets, appetite swells for human-centric AI arrangements that accommodate spoken-language operation, deliberative agents, and flexible pipeline composition.

The arrival of Large Language Models (LLMs) [10, 11] and Generative AI (GAI) unlocks fresh avenues for erecting such arrangements. LLMs exhibit pronounced strengths in parsing and producing natural language, permitting lay users to converse with AI assets through dialogue-style exchanges. Once augmented with Retrieval-Augmented Generation (RAG) and autonomous inferential agents, LLMs can equip platforms to understand user objectives, coordinate across interdependent tasks, and orchestrate sequential AI procedures. This vision carries particular resonance for energy scenarios, where disciplinary intricacy and staffing shortfalls commonly slow down AI deployment.

To confront these hurdles, the X-AI environment is introduced—a process-oriented, end-to-end artificial intelligence ecosystem engineered to fast-track digital evolution across the energy landscape. Within this manuscript, X-AI serves as the designation for the proposed visual AI ecosystem. The acronym signifies an “eXplainable Artificial Intelligence” ecosystem and encapsulates the convergence of graphical model design, sector-specific AI building blocks, and intelligent assistants powered by LLMs [10, 11]. The driving purpose behind X-AI is to make intelligent model development attainable, transparent, and efficient for energy practitioners through a people-first, code-absent setting. Throughout this text, X-AI denotes the ecosystem in its entirety, spanning its graphical interface, computational core, and the integrated intelligent assistant, Dragon Dawn (D2). To heighten ease of use, we unveil D2, an intelligent assistant constructed atop LLMs and logic-driven agent frameworks. D2 permits dialogue-based exchanges, autonomous data probing, and self-acting pipeline formulation. Moreover, we advance a novel indicator, the Cognitive-Operation Efficiency Ratio (COER), to appraise the ecosystem’s usability by encompassing both task productivity and mental exertion.

Furthermore, X-AI is expressly crafted for the energy domain. It unifies a suite of field-tested models, such as inflow prediction and inverter malfunction identification. It also provides a repertoire of all-purpose computational functions—among them Fourier transforms, decomposition algorithms, and symbolic equation solvers—adapted to varied energy modalities, including wind, solar, hydro, thermal, and storage. For physics-grounded modeling, X-AI supplies building

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blocks for computation, equation resolution, and physical constraint articulation, permitting the composition of blended physics-informed and mathematical modeling sequences. Additionally, energy-domain conceptual frameworks are intricately woven into the system's interaction architecture and operator specifications. The intelligent assistant D2 further deepens this sector alignment by drawing upon vectorized knowledge collections assembled from authoritative documents and manuals spanning multiple energy subdisciplines.

We corroborate the ecosystem's merit through a case investigation centered on hydropower inflow prediction, a linchpin of reservoir management and power scheduling. The analysis juxtaposes conventional LSTM-centered development with XGBoost workflows mentored by D2, showcasing how dialogic AI assistants can improve forecasting accuracy, reduce modeling costs, and enhance system usability. This investigation contributes to the expert systems discipline by revealing how LLMs and intelligent assistants can enrich established AI ecosystems, lifting their accessibility, self-sufficiency, and real-world efficacy within industrial realms.

This inquiry advances the energy AI frontier by demonstrating how LLM-steered assistants can be interlaced into applied ecosystems to equip domain engineers, diminish adoption impediments, and enhance intelligent modeling across industrial energy settings.

Technical Framework of the X-AI Platform

This segment acquaints readers with the X-AI ecosystem, emphasizing conversational intelligence.

Transformer-based architectures for language understanding

To facilitate natural language manipulation and modeling operations within energy contexts, LLMs form the backbone of X-AI's intelligent assistant component. These models are erected upon the Transformer blueprint [12], a sequence-to-sequence paradigm that has displaced earlier Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) across the majority of Natural Language Processing (NLP) undertakings, thanks to its scaling potential and performance edge.

As shown in **Figure 1**, the Transformer relies heavily on the self-attention procedure, which captures contextual relationships within input streams without resorting to recurrence. This unfolds across numerous multi-head attention tiers, empowering the model to attend to distinct semantic dimensions in parallel. To safeguard ordering cues forfeited through non-sequential treatment, positional encodings are affixed to input embeddings.

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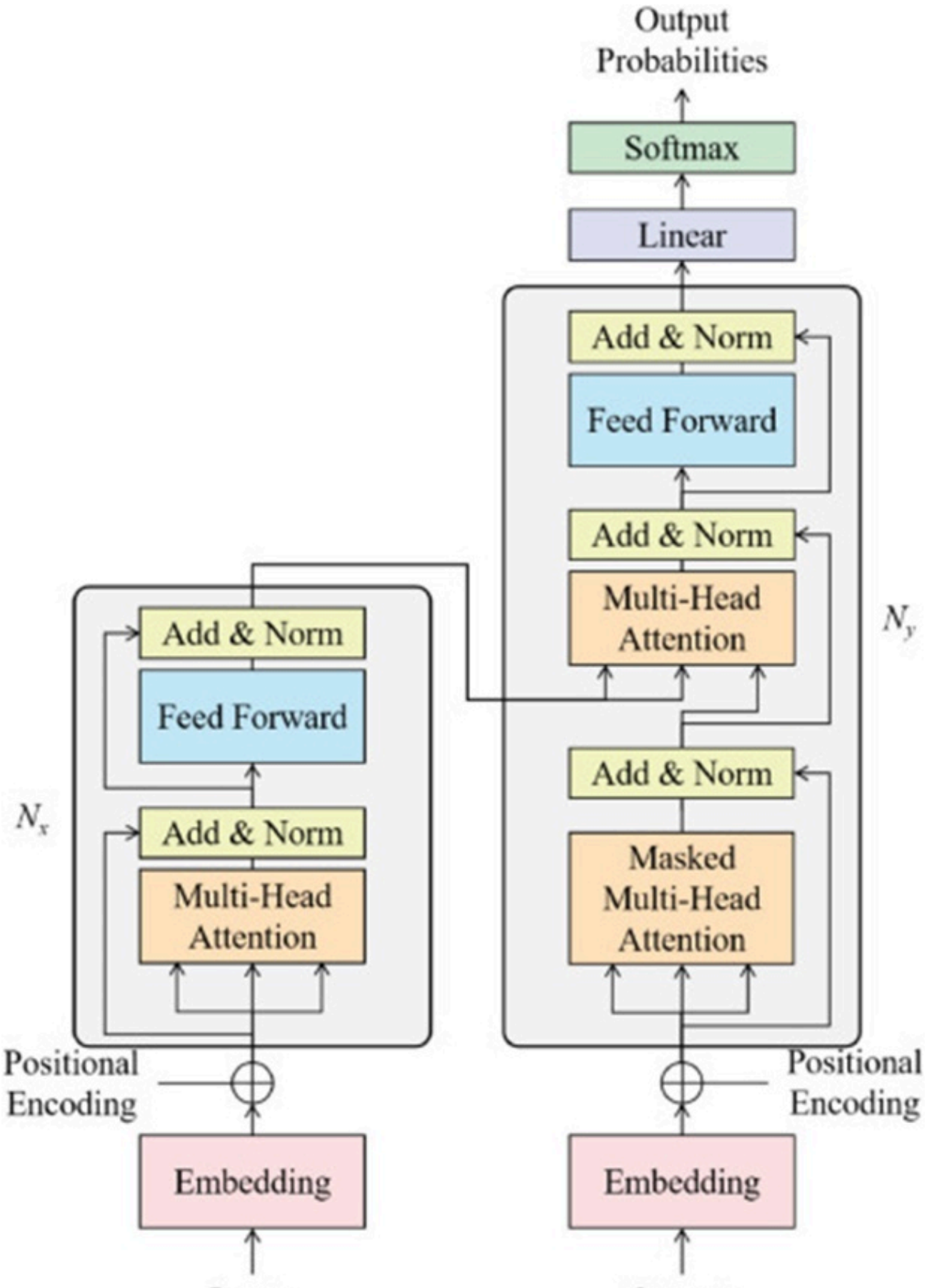

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Inputs Outputs
(Shifted right)

$$\text{Attention}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V} \quad (1)$$

With D, K, and V signifying the query, key, and value arrays, respectively. These tiers get fused and dispatched through a fully connected layer, constituting the backbone of multi-head attention.

For this work, we select the Qwen2.5–72B model due to its strong function-invocation prowess, contextual grasp, and domain-attuned inference, making it well-suited for energy-sector conversational tasks.

Retrieval-augmented generation for knowledge integration

Notwithstanding their broad capability, LLMs regularly contend with stale information, confabulation, and sector misalignment [13, 14]. To remedy these pitfalls, X-AI embeds RAG [15], a fusion strategy that bolsters LLM generations with live information lookups.

As portrayed in **Figure 2**, the RAG arrangement merges two foundational operational blocks to underpin knowledge-rooted inferencing. The first is the lookup block, which uses dense vector encodings (embeddings) to semantically search and extract relevant documents from organized repositories or unstructured text stores. This step ensures that user inquiries gain contextual enrichment from highly matched material. The second is the synthesis block, which ingests the original user inquiry alongside the fetched material and yields lucid, context-aware replies. By wedging semantic lookup with generative synthesis, the RAG framework enables outputs that are sharper, more interpretable, and better anchored in facts.

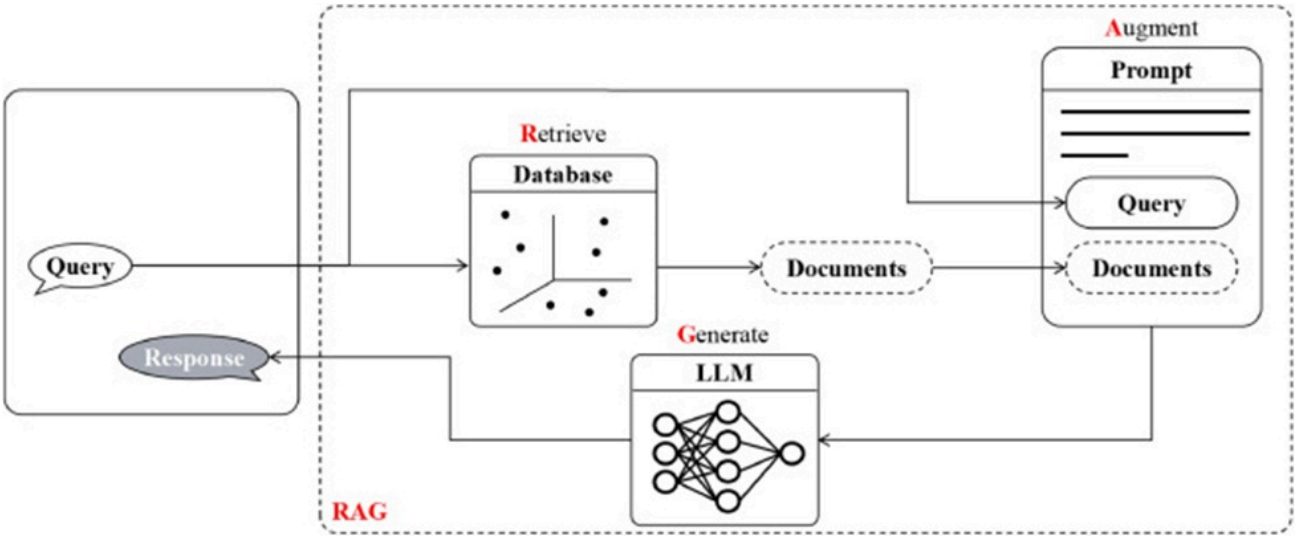

Figure 2. RAG flowchart.

To quantify document pertinence, X-AI wields Maximal Marginal Relevance (MMR) [16]:

$$s(\mathbf{q},\mathbf{d}) = \frac{\text{sum}(\mathbf{q}\cdot\mathbf{d})}{\|\mathbf{q}\|\cdot\|\mathbf{d}\|} = \frac{\sum_i (q_i \cdot d_i)}{\sqrt{\sum_i q_i^2}\cdot\sqrt{\sum_i d_i^2}} \quad (2)$$

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$$\mathrm{MMR}(\mathbf{q}, \mathbf{d}_i) = \underset{d_i \in D}{\mathrm{arg}max}\left[\lambda \cdot s(\mathbf{q}, \mathbf{d}_i) - (1-\lambda) \cdot \max_{\mathbf{d}_j \in R} s(\mathbf{d}_i, \mathbf{d}_j)\right] \quad (3)$$

Where λ governs the trade-off between relevance and diversity.

Through RAG, sector-specific intelligence can be woven into the LLM's reasoning trajectory without model retraining, elevating timeliness, specialism, and factual dependability.

Intelligent agent-based reasoning and control

To enable self-directed decision-making and conversational modeling within energy systems, X-AI incorporates an intelligent assistant stratum that administers task orchestration, multi-hop inferencing, and context-adaptive tool activation via natural language discourse. This is crucial in energy undertakings like scheduling and forecasting, where modeling sequences must remain nimble and be steered by domain-coded objectives.

Multi-modal knowledge integration for energy contexts

In tangible energy deployments, intelligent assistants must tap into and reason over disparate data modalities, including structured corporate stores (e.g., relational repositories), freeform records (e.g., operator handbooks), and vectorized knowledge bases (e.g., engineering schematics or RAG-encoded dossiers). To this end, the X-AI agent framework enables: fetching energy-domain know-how from handbooks, documentation, and enterprise repositories; decoding operator aims via LLM-grounded natural language comprehension; and adaptively rendering elevated user prompts into performable actions like SQL queries, drag-and-drop modeling operations, or API summons.

This gets realized through a consolidated agent orchestration fabric, capable of dissecting prompts, summoning appropriate tools, and stewarding outputs across modalities. Compared with static workflow engines, this design enables malleable behavior shaped by shifting user objectives and data milieus.

ReAct agents for autonomous task execution

Nestled at the heart of the intelligent control stratum is a Reasoning and Acting (ReAct) agent [17], which oscillates between cognitive strategizing and action fulfillment. As visualized in **Figure 3** and **Table 1**, the ReAct agent accomplishes tasks via an iterative feedback loop constituted by:

1. Thought: The LLM deciphers the operator's objective and designates a fitting tool.

2. Action and input: The tool gets activated using the synthesized parameters.

3. Observation: The result undergoes assessment and re-enters the inferencing cycle.

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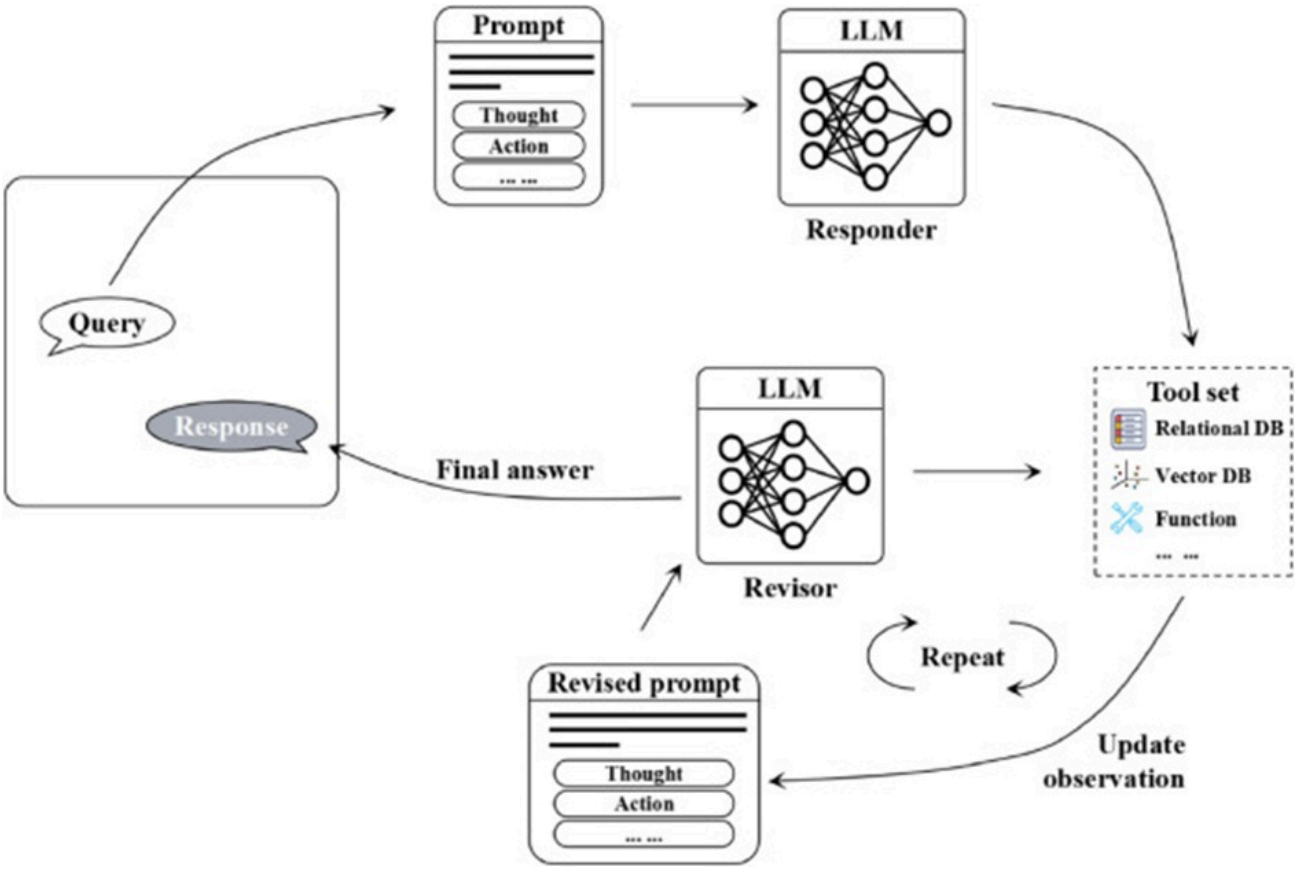

Figure 3. The ReAct flowchart.

Table 1. The ReAct process.

Require: *T*, tool descriptions; *S*, maximum thought iterations; P_{init}, initial prompt; *llm*, Qwen2.5–72B; *O*, final response.
1. Use a JSON-like data structure to construct *T*, which contains descriptions of all tools. Each tool's entry should include the tool name, description, and parameters. Parameters must be represented as a key-value dictionary, with the keys indicating parameter names, descriptions, and data types.
2. Construct the initial prompt P_{init} using *T*. This prompt instructs Qwen2.5–72B to process the input query through stages of thought, action, action input, and observation. The process may repeat zero or more times.
3. Set $P = P_{init}$
4. **while** $s < S$ **do**
5. $r = llm(P)$
6. Extract the tool name *t* from the action in *r* using string processing.
7. **if** *t* is "FINISH"
8. **end while**
9. **else**
10. Extract tool parameters *p* from the action input in *r* using string processing.
11. Execute the corresponding tool based on *t* and *p*. The tool result is r_t.
12. Update the observation content in *P* with r_t.
13. $s = s + 1$
14. **end if**
15. **end while**
16. Set $O = r_t$

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This loop persists until a FINISH signal is dispatched, enabling comprehensive task realization with traceable reasoning footprints. Tool definitions conform to a JSON-structured schema, enumerating tool labels, parameter outlines, and anticipated outputs.

This agent blueprint unlocks several cardinal operations integral to X-AI's role in energy-sector contexts. A flagship capability is Text-to-SQL (Text2SQL) rendition, permitting operators to pose natural language interrogations that automatically convert into executable SQL syntax for extracting information from relational data stores. This markedly softens the entry threshold for lay users seeking structured data access. Furthermore, the assistant enables the assembly of modeling pipelines via conversational discourse. Operators can convey their modeling intents in plain prose, and the assistant adroitly composes corresponding nodes upon a visual workspace. Additionally, by capitalizing on RAG, the assistant can summon and deploy sector-specific intelligence throughout the modeling lifecycle, enhancing both fidelity and intelligibility.

By interweaving ReAct agents into the ecosystem, X-AI equips domain engineers to carry out intricate modeling and decision-support operations across energy settings absent any programming, thereby abating technical barriers and hastening AI assimilation throughout power systems.

Dragon dawn: an LLM-Powered agent for energy modeling

To materialize the intelligent agent framework inside X-AI, we instantiate D2, a sector-attuned assistant sculpted to serve energy engineers through natural language discourse. As depicted in **Figure 4**, D2 operates as a semantic conduit bridging operators and platform functionalities, conferring instinctive access to modeling utilities, data repositories, and domain expertise.



Figure 4. The D2 agent for the X-AI platform.An LLM energizes D2 and meshes two principal knowledge founts to navigate a spectrum of energy-focused undertakings:

• A vector repository, Milvus [18], which indexes operator handbooks, platform documentation, and common inquiries, enabling swift semantic retrieval via resemblance matching.

• A Relational Database Management System (RDBMS), My Structured Query Language (MySQL) [19], which warehouses structured enterprise archives, encompassing intellectual property dossiers, contract particulars, staff

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designations, and project hierarchies.

By fusing LLM inferencing with Text2SQL dexterity, D2 morphs natural language interrogations into syntactically valid SQL expressions. For example, requesting the identities of project leads assigned to a given hydropower undertaking requires no manual scripting; the assistant infers the operator's intent, maps it to the relevant table schema, and yields a valid query. Via this construct, D2 substantially lifts the approachability, throughput, and scaling potential of AI modeling sequences within energy settings. Beyond inferencing and interrogating, D2 can outright operate the ecosystem's visual workspace, interlink pipeline constituents, and automate project execution, thereby functioning as a fully end-to-end modeling aide for energy deployments.

Dragon Dawn behavior and limitations

To secure resilience and versatility in practical deployments, D2 weaves together an array of mechanisms addressing feedback-guided correction, fault endurance, and conversational steadiness within energy modeling operations.

One prominent capability is the operator evaluation and continuous enhancement loop. Specifically, each time D2 crafts a SQL statement from a natural language expression, operators may appraise the output using an embedded scoring widget. When a query is confirmed accurate, the ecosystem archives the operator's original phrasing, along with the LLM-generated SQL counterpart, into a curated exemplar bank. In later Text2SQL sessions, the platform gauges semantic proximity between new utterances and archived exemplars via vector embeddings. The closest-matching precedents are then interleaved into the prompt as few-shot demonstrations, enabling the model to absorb patterns from previously successful dialogues and incrementally elevate translation exactness. This scheme erects a functional retrieval-anchored recollection tuned to domain-specific interaction patterns.

To strengthen dependability, D2 additionally enacts recovery and self-stabilizing maneuvers across multi-phase pipelines. When an instrument call malfunctions—triggered by factors including datastore timeouts, malformed arguments, or void returns—the assistant can revisit the preceding inferential segment, recalibrate the operation or its parameters, and reattempt execution. These intrinsic safety nets safeguard workflow continuity amid transient or unclear circumstances.

The platform further facilitates context-coherent exchanges via conversation-scoped memory and status tracking. D2 preserves short-range dialogue chronicles, modeling directives, and interim outcomes, enabling fluid multi-turn engagements. For instance, if an operator references "the preceding model" or issues an ambiguous command such as "tune this projection," D2 uses conversation memory to reconstruct relevant context and emits clarifying prompts when warranted. This bolsters both precision and operator assurance during recurring modeling duties.

That being said, the D2 assistant bears inherent boundaries—the ceiling of the underlying LLM hems in its symbolic manipulation and formulaic derivation capacities. Intricate mathematical formulations, multi-hop derivations, or tightly precise numerical outputs continue to pose difficulties, as is typical of LLMs. Additionally, while D2 amalgamates knowledge corpora across multiple energy subdomains, the existing documentary span is richest for hydropower. Subdomain-specific manuals, engineering protocols, and project repositories for solar, wind, thermal, and storage remain under incremental ingestion. As a consequence, D2 may display dampened capability or conviction when addressing advanced modeling interrogations linked to those subdomains. We view this as an unfolding trajectory of progressive enrichment and adaptive maturation.

Platform Usability Evaluation

To gauge the pragmatic utility of X-AI for energy system modeling activities, we undertake a holistic appraisal blending impartial task benchmarks with mental exertion metrics. In energy settings, AI tools must marry accuracy with accessibility for domain specialists operating under temporal and complexity pressures. Accordingly, we advance a hybrid

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measurement paradigm encompassing conventional performance yardsticks alongside a newly propounded indicator termed the COER.

Effectiveness and efficiency metrics

The principal gauges for usability measurement are Task Completion Rate (TCR), Task Execution Time (TET), and Number of Steps (NOS):

• TCR captures the proportion of assignments successfully concluded, signaling the ecosystem's overall robustness and operator accessibility.

• TET gauges the mean span consumed per assignment.

• NOS enumerates the count of operator interactions necessary to finalize an assignment.

A lower NOS value points to a more intuitive pipeline design, a vital property when fielding AI models inside intricate energy infrastructures where time constraints and interpretability hold sway.

$$\mathrm{TCR} = \frac{n_{success}}{n_{total}} \quad (4)$$

$$\mathrm{TET} = \frac{\sum_{i=1}^{n} T_i}{n} \quad (5)$$

$$\mathrm{NOS} = \frac{\sum_{i=1}^{n} S_i}{n} \quad (6)$$

Where Ti signifies the span consumed for each assignment; Si signifies the interaction count per assignment; and n indicates the tally of assignments concluded.

To determine statistical meaningfulness, a two-tailed t-test [20] is conducted:

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}} \quad (7)$$

Where $\overline{X}_1$ and $\overline{X}_2$ denote group averages before and after enhancement; σ_1^2 and σ_2^2 represent variances; and n1 along with n2 indicate sample magnitudes.

As set out in **Table 2**, evaluations cover 32 representative assignments, including model training, cluster examination, and feature engineering. The D2-enhanced ecosystem posted statistically meaningful advancements across all three gauges. These findings verify that integrating LLMs and inferential agents within expert-oriented frameworks can markedly elevate usability and operational throughput.

Table 2. Evaluation results.

Empty Cell	**Significance**	**Improvement**	**D2-enhanced X-AI**	**X-AI**

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TCR	$p < 0.01$	+23.3 %	91.5 %	74.2 %
TET	$p < 0.01$	−43.6 %	9.3 min	16.5 min
NOS	$p < 0.01$	−54.3 %	5.8 steps	12.7 steps

Cognitive-operation efficiency ratio

Distinct from established usability scores, COER captures both how productively an operator can wrap up an assignment and how mentally taxing that assignment feels. This dual lens carries particular salience in energy-industry environments, where engineers juggle AI tool interaction alongside multiple operational responsibilities.

$$\mathrm{COER} = \frac{E_{op}}{C_{load}} \quad (8)$$

Where Eop reflects operational productivity, synthesized from TET and NOS; and Cload reflects mental burden, blending subjective and behavioral indicators.

Operational efficiency

Eop is derived from TET and NOS:

$$E_{op} = z(\mathrm{TET}) + z(\mathrm{NOS}) \quad (9)$$

Where z indicates z-score normalization, reshaping each variable into a dimensionless metric referenced against its own mean and standard deviation. This construction permits merging disparate indicators bearing different units and distributions into a single productivity score.

Cognitive load evaluation

Mental burden Cload constitutes a weighted composite of subjective load and behavioral load:

$$C_{load} = \alpha C_{subjective} + (1 - \alpha) C_{objective} \quad (10)$$

Where α ∈ {0.3, 0.5, 0.7}.

Subjective load Csubjective is captured through the NASA Task Load Index (NASA-TLX) [21] instrument spanning six facets (mental demand, physical demand, temporal demand, performance, effort, frustration). 47 operators complete the questionnaire, and readings undergo normalization (0–1 band).

Behavioral load Cobjective is estimated via interaction proxies [1]:

1. Instability in Task Completion Time

2. Fault Ratio

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3. Task Interruption Incidence

4. Click Trajectory Entanglement

Where Tcompletion denotes an assignment's finish duration; nerror denotes the count of erroneous moves; nt indicates total action count; npause denotes the count of interruptions within an assignment; ttask denotes the time window; nactual_clicks denotes actual click count, and noptimal_clicks equals the click tally of the minimal path.

The formulation for Cobjective reads:

$$C_{objective} = z(V_{time}) + z(E_{rate}) + z(P_{count}) + z(C_{complexity}) \quad (11)$$

Results and analysis

As borne out in **Table 3**, the D2-enhanced ecosystem substantially trimmed both mental strain and operational expense. Under varying α values, the COER gain with D2 remained stably elevated (ranging between 6.5× and 8.2×).

Table 3. Evaluation of the COER.

Metric	D2-enhanced X-AI	Initial X-AI
E_{op}	0.01854	0.00477
$C_{subjective}$	0.12	0.71
$C_{objective}$	0.04	0.45

This inquiry puts forward the COER metric as an innovative appraisal scaffold that welds operational execution and user cognition into a unitary, interpretable index. In contrast to long-standing usability benchmarks, COER unlocks fine-resolution gauging of both system refinement and user encumbrance—a property especially germane in intricate expert-oriented systems featuring human-in-the-loop configurations.

These outcomes bear out that embedding LLM-powered assistants into AI modeling ecosystems can substantially shrink the cognitive barrier confronting energy professionals. The nearly 8.2-fold elevation in COER signals not merely sharper assignment execution but widened accessibility for non-AI operators. This bears direct implications for accelerating intelligent system fielding across the energy landscape, particularly in scenarios where operational throughput and operator endorsement hold decisive weight. Furthermore, the propounded COER metric offers a portable methodology for evaluating human-focused AI instruments throughout industrial contexts.

System Architecture and Functional Design of X-AI

This segment furnishes an elaborate portrayal of the architecture, user interface, and modeling repertoire of the proposed X-AI ecosystem. Emphasis rests on how the system design harmonizes with expert-system precepts—modular decomposition, human-machine dialogue, domain knowledge encapsulation, and intelligent workflow orchestration.

Platform architecture

Technology stack

As illustrated in **Figure 5**, X-AI embraces a current-generation, modular technology stack suited to cross-platform delivery via mainstream browsers (e.g., Chrome and Firefox). The ecosystem employs a modular, web-native architecture that

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enables cross-platform accessibility and elastic backend provisioning, ensuring dependable completion of energy modeling pipelines.

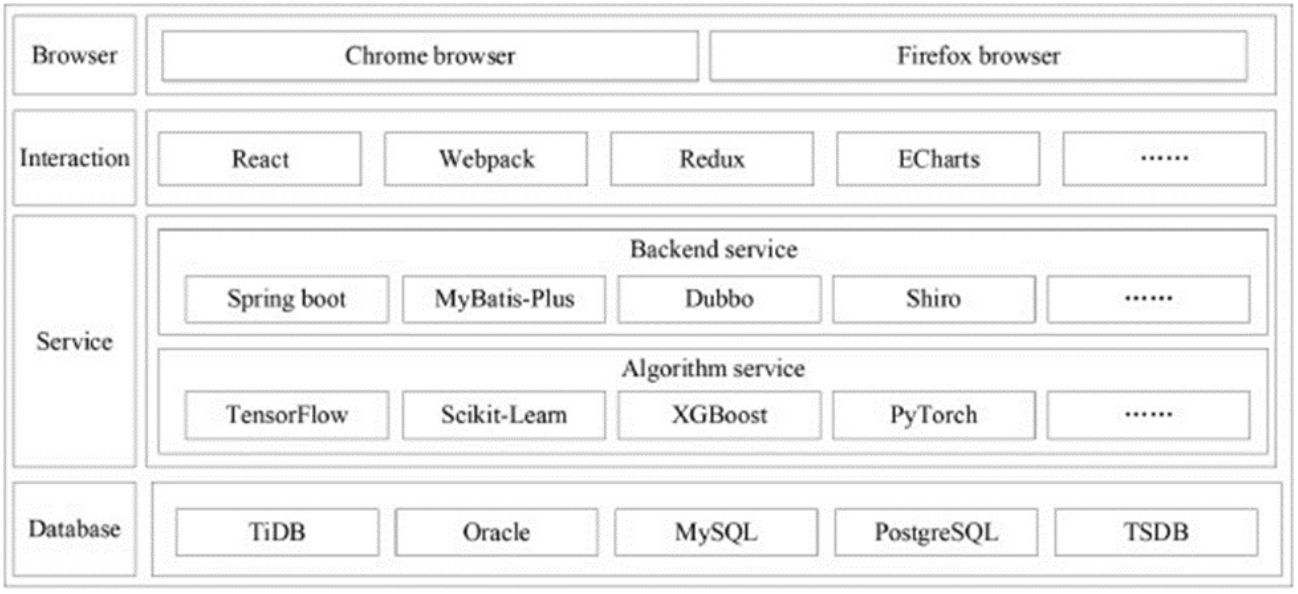

Figure 5. X-AI technology stack and integration architecture.

The ecosystem's backend is buttressed by a resilient technical base that furnishes protection, growth capacity, and adaptability. Operator identity and entitlement governance are administered through Shiro, while dispersed services are deftly coordinated via Dubbo. For front-end rendering and operator interaction, the ecosystem harnesses ECharts for rich graphical displays and Webpack for lean asset consolidation. On the algorithmic side, the platform incorporates widely adopted machine learning frameworks—spanning TensorFlow, PyTorch, XGBoost, LightGBM, and Scikit-Learn—to serve heterogeneous modeling requirements. Data governance pivots on TiDB as the core storage foundation, augmented by smooth assimilation of varied data origins such as Oracle, MySQL, PostgreSQL, and time-series repositories through RESTful APIs, enabling real-time and archival data fusion for AI workloads.

Layered functional architecture

As rendered in **Figure 6**, the foundational design of X-AI is partitioned into six interlinked tiers: applications, functional modules, operator libraries, algorithm engine, data services, and infrastructure.

• Application tier: Trained artifacts are operationalized within archetypal energy settings, encompassing hydropower inflow estimation, power infrastructure fault detection, and energy performance diagnostics.

• Function tier: Encompasses identity administration, project coordination, model fitting and serving, artifact versioning, job dissemination, and shared environments. Bespoke functionalities extend to image/text annotation and modular retrieval of platform documentation.

• Operator tier: Houses recyclable components classified into data intake, preprocessing, feature derivation, clustering, model construction, dependency measurement, performance yardsticks, and sector-customized operators.

• Algorithm engine: Abstracts and provisions an extensive catalog of ML/DL constructs.

• Data tier: Fuses structured repositories with unstructured feeds and streaming time-series stores.

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• Infrastructure tier: Maps computational workloads onto suitable hardware substrates (CPU, GPU), facilitating elastic resource allocation calibrated to demand fluctuations.

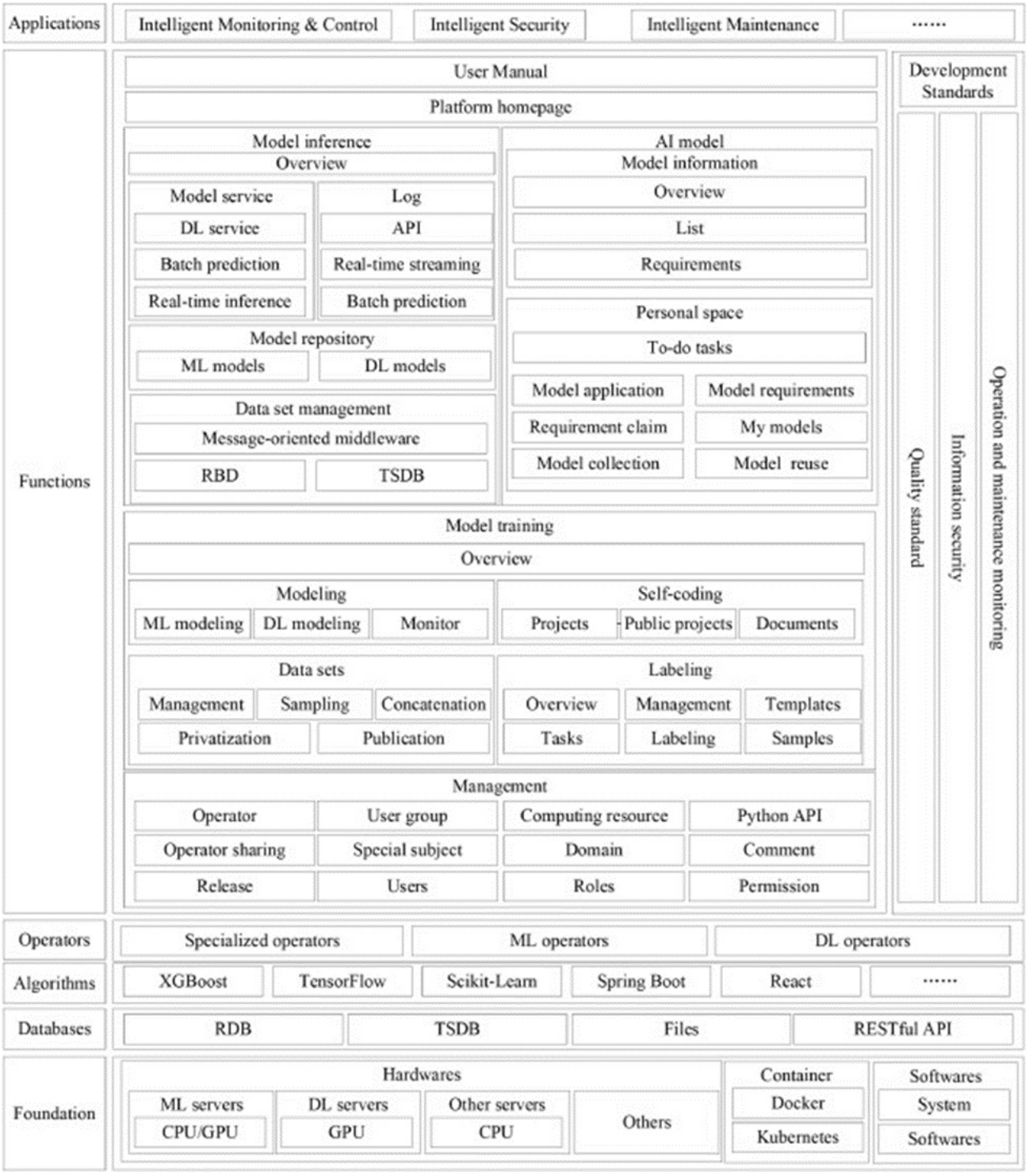

Figure 6. Functional architecture of the X-AI platform.

Workflow-oriented data stream

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To deliver ease of use and operational fluency within production energy environments, the ecosystem adopts a pipeline-driven, role-partitioned orchestration model that cleanly separates the remits of practitioners and system stewards. As pictured in **Figure 7**, practitioners are authorized to assemble and steer modeling workflows, import data origins, launch training cycles, and surface validated artifacts into the shared repository. They may likewise propose new modeling assignments or adopt unclaimed ones, fostering joint development and expertise exchange. Concurrently, system stewards govern overall platform vitality, vet submitted tasks and artifacts, maintain the operator collection, apportion compute capacity, and uphold quality governance measures. This orderly division of duties permits smooth pipeline realization and ensures high dependability in AI-powered energy undertakings.

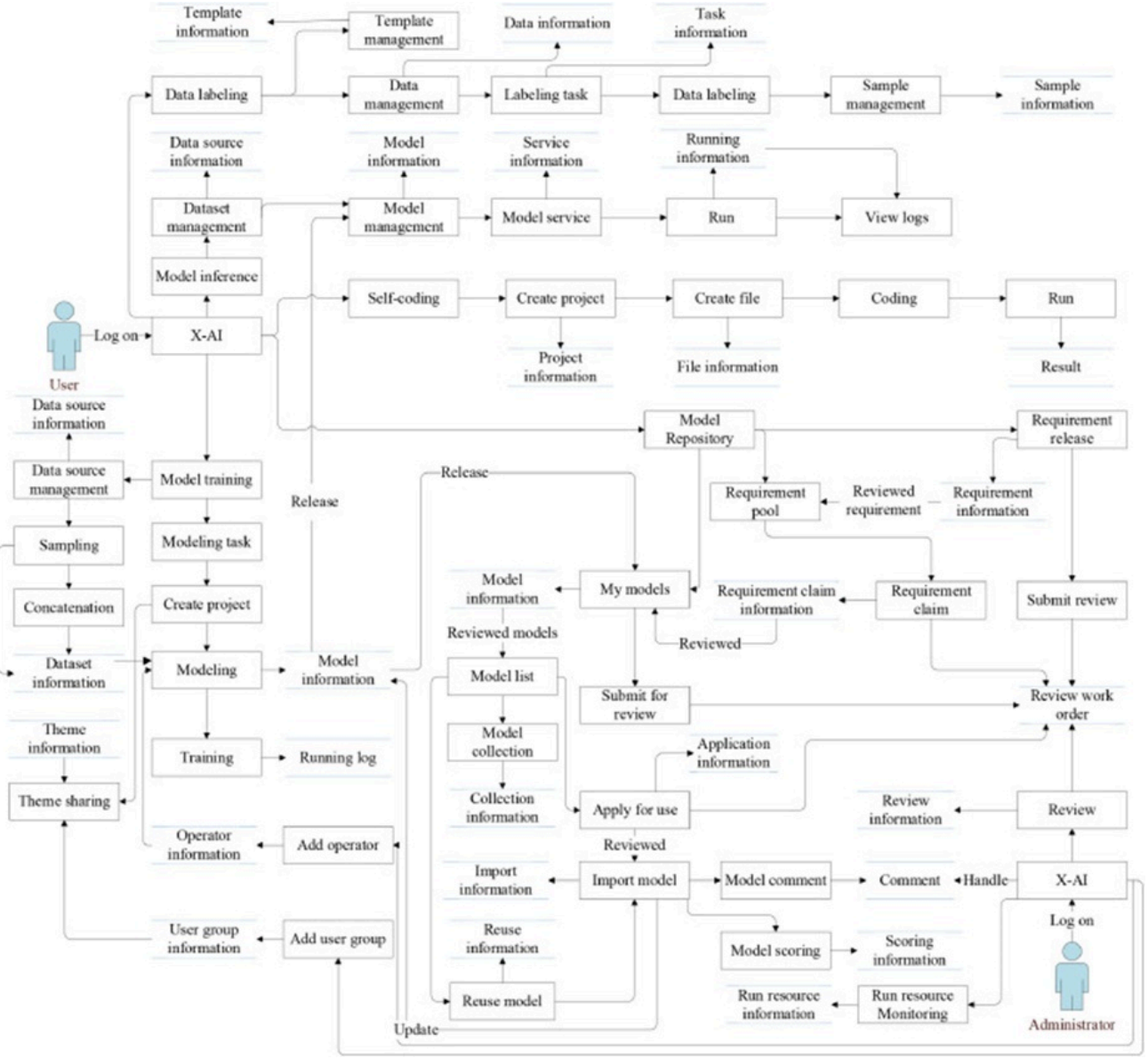

Figure 7. Role-driven data flow within X-AI.

Interface design and workflow construction

X-AI supplies a graphical assembly workspace that encodes disciplinary expertise into visual primitives. Practitioners piece together AI pipelines via drag-and-drop composition, curtailing dependence on coding proficiency and quickening artifact deployment. The visual workspace packs intricate modeling phases into instinctive, drag-and-drop gestures,

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equipping energy engineers to devise intelligent workflows with negligible handcrafted code. As depicted in **Figure 8**, the left sidebar exhibits categorized operator palettes, the upper ribbon grants access to job execution, log inspection, project preservation, and similar functions, while the bottom panel enables nimble canvas operations (e.g., view scaling, undo/redo, component linking). This code-absent workspace supports incremental pipeline assembly and visual fault tracing.

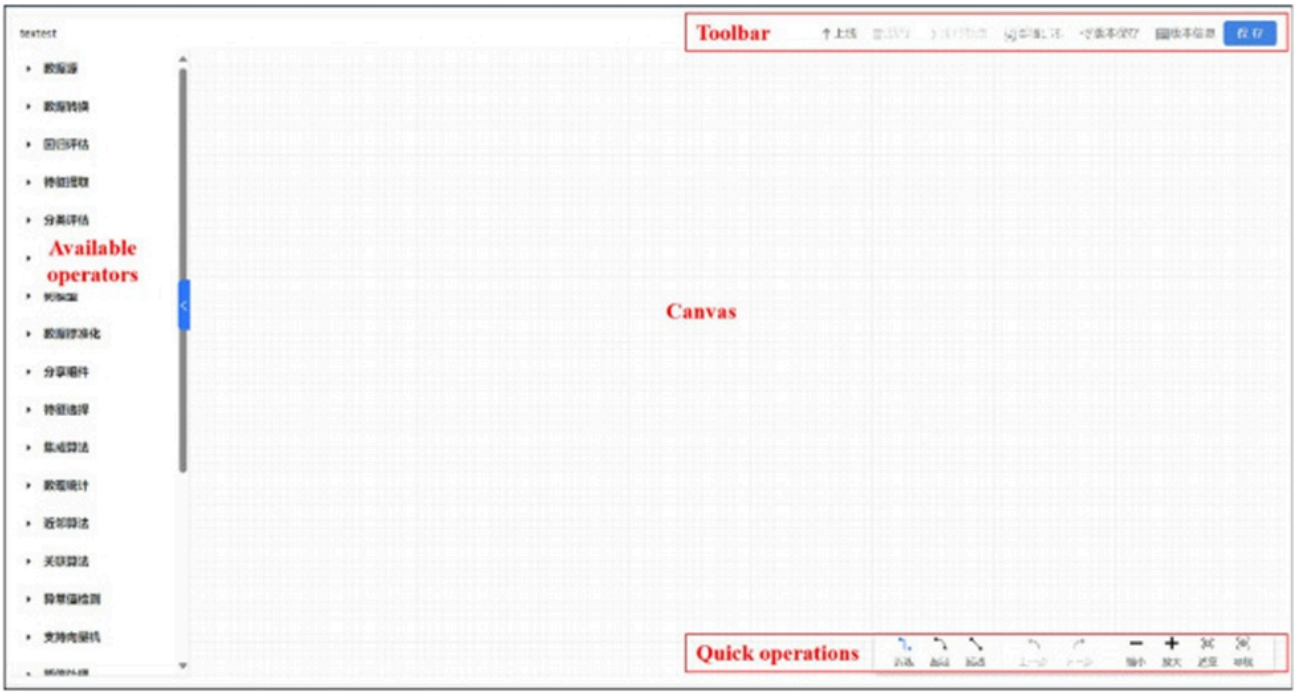

Figure 8. User interface for visual modeling in X-AI.

AI-driven modeling workflow

Modeling algorithms

As cataloged in **Table 4**, X-AI unifies north of 40 general-purpose ML/DL formulations alongside energy-attuned operator modules. Beyond these, over 100 domain-specific artifacts calibrated for power generation contexts—including inflow projection, frequency stabilization, and malfunction isolation—are embedded. Symbolic equation solvers, numeric integration routines, and constraint specification modules permit the articulation of physics-rooted relational models.

Table 4. Categorized algorithms integrated into X-AI.

Category	Methods
Tree-based algorithms	Decision Tree (DT) [22] Random Forest (RF) [23] Extremely Randomized Trees (ERT) [24]
Neural network approaches	Backpropagation Neural Network (BPNN) [25] Inception V3 [26] ResNet [27] Visual Geometry Group (VGG) network [28] GoogLeNet [29] Long Short-Term Memory (LSTM) network [30]
Support Vector Machine (SVM)-based techniques	Support Vector Machine (SVM) [31] Least Squares Support Vector Machine (LSSVM) [32] Relevance Vector Machine (RVM) [33]

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Boosting-based methods	Adaptive Boosting (AdaBoost) [34] Gradient Boosting [35] CatBoost [36] eXtreme Gradient Boosting (XGBoost) [37] Light Gradient Boosting Machine (LightGBM) [38]
Energy-domain analytical operators	Fourier Transform techniques Wavelet-based analysis Empirical Mode Decomposition (EMD) Seasonal and Trend Decomposition using Loess (STL) Kalman Filtering Delay Embedding methods
Application-specific models	Curve-fitting models for irradiance–power and irradiance–current relationships Feature-coefficient computation for power and current correction factors Fault early-warning systems for inverter error codes E201, E202, E301, E302, D101, D201, D202, and related faults Prediction models for inflow, wind generation, electrical load, and similar variables Water and steam property calculation functions Multivariate state estimation and early-warning frameworks Primary frequency regulation models Policy-data transformation functions Maximum operational output estimation Maximum available output estimation Load deviation diagnostic models

To pare down modeling intricacy, Automated ML (AutoML) [39] is employed via evolutionary optimization for hyperparameter search, guided by F1-score as the objective criterion.

Feature engineering

Feature engineering within the ecosystem is materialized through a modular scaffold that disentangles predictor selection from predictor extraction procedures. For predictor selection, practitioners may invoke methods including SelectKBest [40], SelectFwe [41], and Recursive Feature Elimination (RFE) [42] to efficiently shrink data dimensionality by surfacing the most informative variables. For predictor extraction, approaches like Principal Component Analysis (PCA) [43], Independent Component Analysis (ICA) [44], and Non-negative Matrix Factorization (NMF) [45] are offered to yield descriptive, reduced-dimension encodings of the original inputs. This modular schema enables practitioners to trial varied feature strategies without disturbing downstream model constructs.

Correlation analysis

The ecosystem furnishes interpretable association tools for scrutinizing variable interrelations, drawing on Pearson's correlation coefficient [46], Grey Relational Analysis (GRA) [47], and Euclidean distance [48]. These instruments help practitioners grasp predictor interdependencies before model training.

Data preprocessing

To condition inputs for ML pipelines, X-AI accommodates robust normalization [49] together with max-min rescaling. The ecosystem likewise provisions interpolation algorithms, encompassing polynomial interpolation [50], B-spline interpolation [51], Radial Basis Function (RBF) interpolation [52], and nearest-neighbor interpolation [53]. These proficiencies bolster model convergence and data integrity.

The blueprint of X-AI is aligned with the operational exigencies of the energy sector, delivering domain-imbued intelligence, practitioner-steered modeling sequences, and viable integration trajectories for intelligent system rollout across hydropower, renewable sources, and grid applications.

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X-AI System Architecture: End-to-End Design for Energy Modeling

This segment presents an exhaustive numerical scenario study that underscores the practical efficacy of the X-AI ecosystem in addressing a concrete industrial challenge—reservoir inflow projection—to support hydropower dispatch refinement. It highlights the ecosystem's modeling prowess, comprehensive pipeline intelligence, and the role of the intelligent assistant D2 in enabling iterative improvement and decision support.

Scenario overview and problem definition

Reservoir Dispatching of Hydropower Station (RDHS) [54, 55] constitutes a mission-critical operational exercise involving the optimized distribution of water assets across electricity generation, flood safeguarding, agricultural irrigation, and municipal supply obligations. A linchpin element of RDHS is inflow projection, which buttresses forward-looking decision-making by estimating upstream water deliveries from rainfall, thaw, and feeder contributions.

Within this study, as portrayed in **Figure 9**, we concentrate on a hydropower installation (Station A) situated amid a cascading reservoir chain in East Asia. The goal is to project the inflow volume arriving at Station A, leveraging archival inflow chronologies, precipitation readings spanning the watershed, and outflow recordings from an upstream installation (Station B). **Figure 9** maps the spatial configuration, whereas **Figure 10** plots inflow observations covering the previous ten years, inclusive of flood-spawned crests.

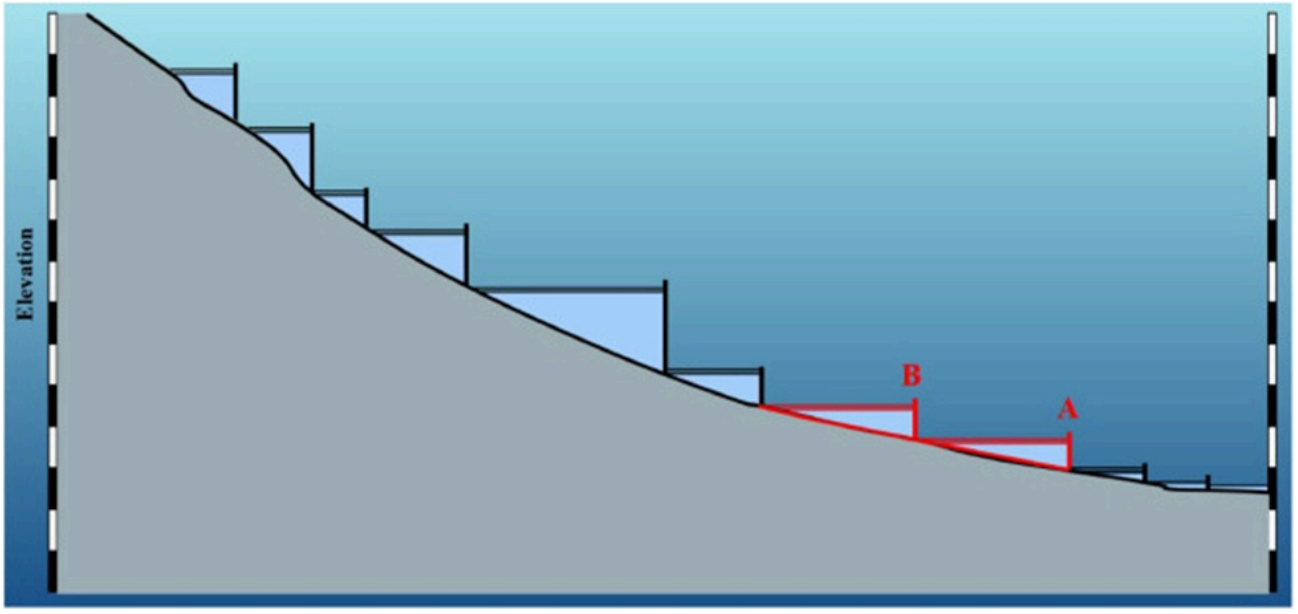

Figure 9. Spatial layout of cascade stations.

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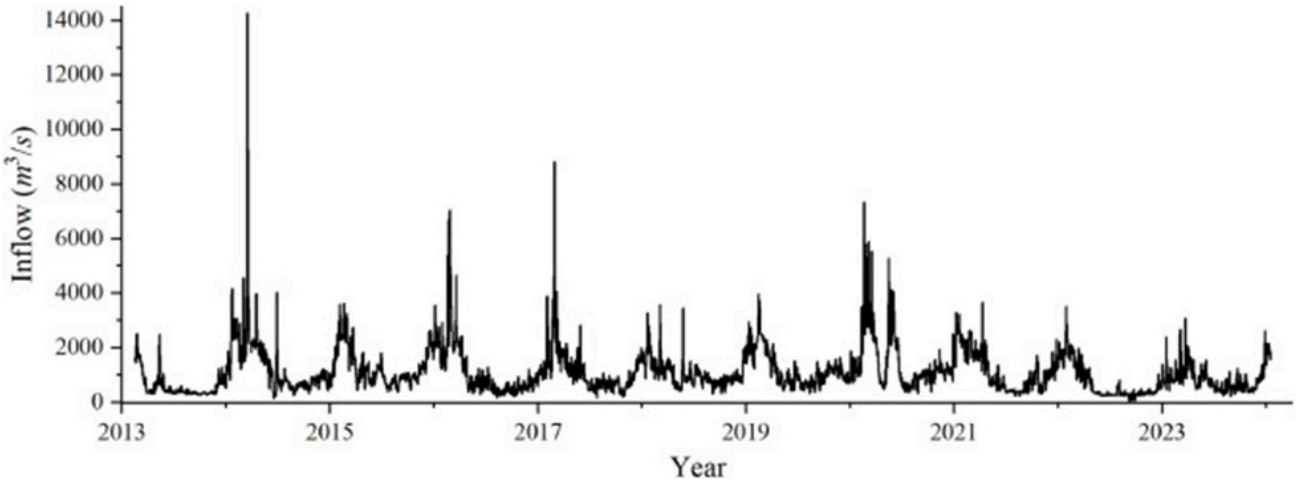

Figure 10. Historical inflow data for Station A.

LSTM-based time series forecasting

Feature engineering and correlation analysis

To reinforce temporal consistency, as illustrated in **Figure 11**, precipitation is accumulated across sliding 2- to 5-day windows. As shown in **Figures 12 and 13**, harnessing X-AI's visual pipeline, Pearson's correlation coefficients between candidate predictors (e.g., cumulative precipitation, upstream outflow) and inflow are computed, informing the variable selection cycle. Pearson's correlation coefficient is derived as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (12)$$

Where x denotes the design variable; y signifies the objective function; and $\bar{x}$ along with $\bar{y}$ indicate the arithmetic means of x and y, respectively.

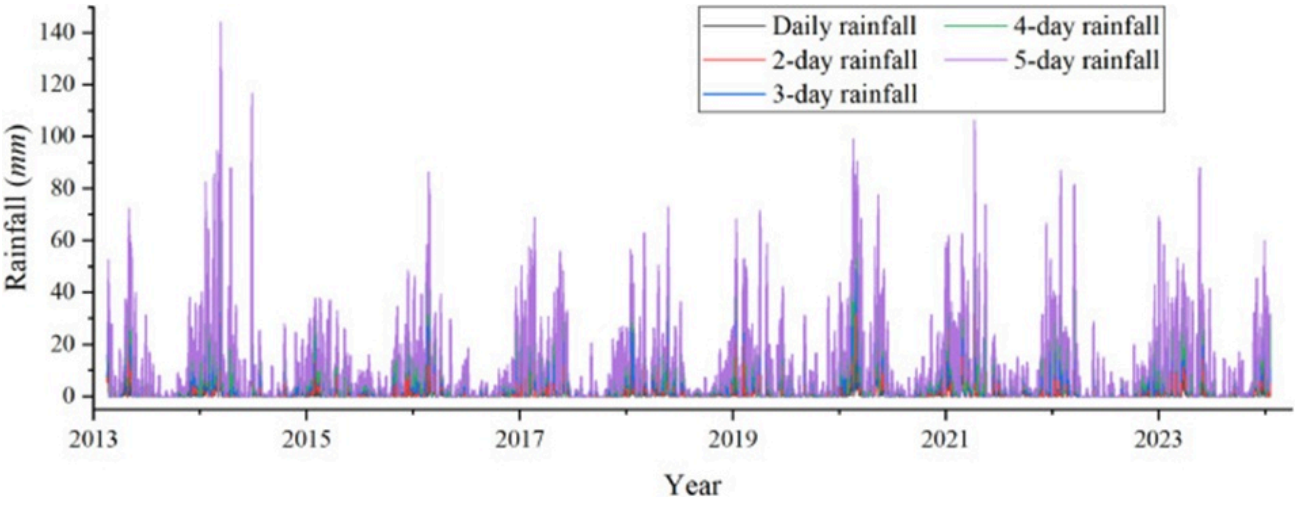

Figure 11. Rainfall and cumulative rainfall.

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Figure 12. Calculation workflow of Pearson's correlation coefficient in X-AI.

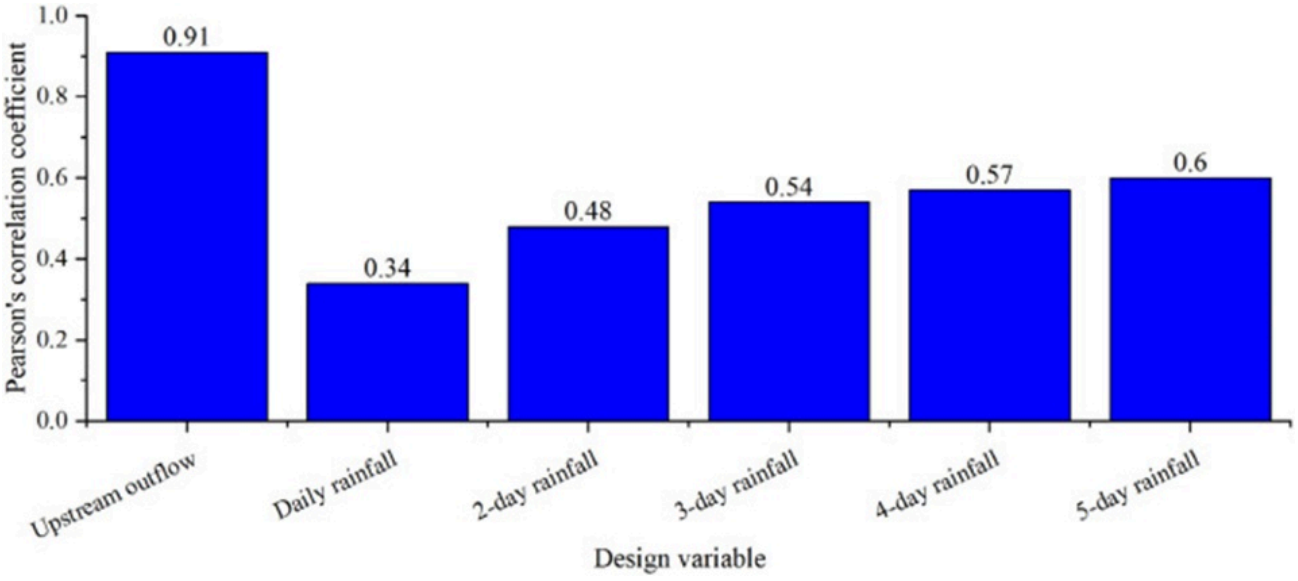

Figure 13. Pearson's correlation coefficient for design variables.

The findings, as illustrated in **Figure 13**, reveal that these six variables display a strong correlation with inflow.

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Workflow construction in X-AI

Thanks to its knack for capturing dependencies across extended temporal spans, LSTM is widely used in hydrological modeling and has posted strong showings in both univariate and multivariate inflow projection undertakings. Practitioners can piece together an LSTM modeling sequence through the graphical canvas of X-AI. As shown in **Figure 14**, the data corpus is split, with 80% allotted for fitting and 20% held back for testing. Input tensors are shaped as 30-timestep windows spanning 7 variables. The prediction target is a 3-step-ahead inflow estimate. The penalty function is designated as Mean Squared Error (MSE).

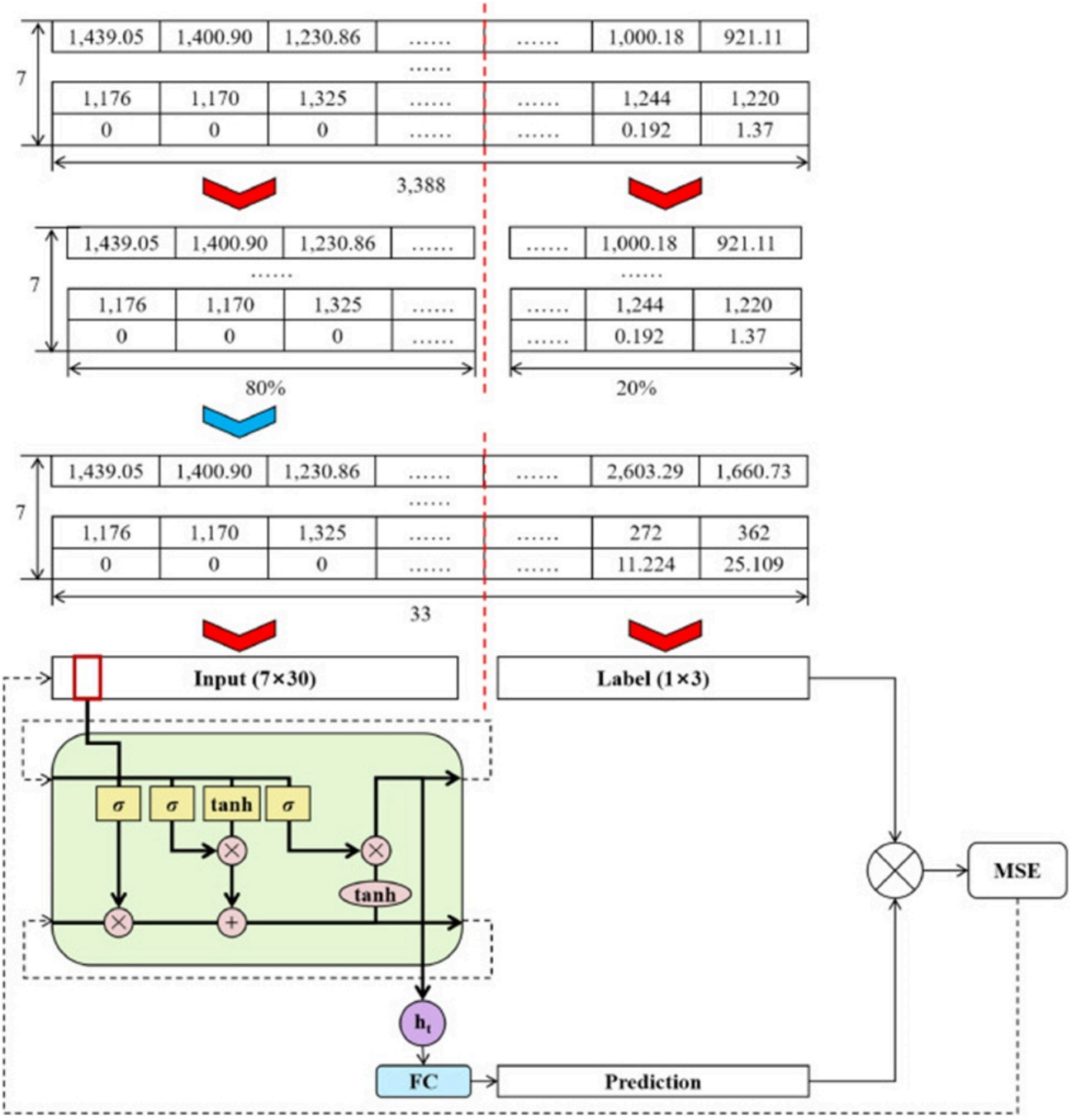

Figure 14. LSTM-based modeling workflow in X-AI.

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Result and evaluation

As sketched in **Figure 15**, the stages below trace the inflow forecasting routine inside X-AI:

· Step 1. A TiDB node is leveraged to pull in the data corpus.

· Step 2. A partition node is dragged onto the workspace. The split fraction is configured at 0.8, meaning 80% of records feed the fitting stage while 20% serve holdout validation.

· Step 3. An LSTM node is activated to project inflow. Its settings are fixed as follows: sequence span equals 30, denoting the input window breadth; target span equals 3; target column offset equals 1, mapping onto the inflow field; the penalty function is MSE; and the dropout proportion is set to 0.5 to temper overfitting.

· Step 4. A metric node is appended to judge the fitted artifact. The assessment criteria are the coefficient of determination (R2) together with Mean Absolute Percentage Error (MAPE).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (13)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (14)$$

where $\overline{y}$ signifies the average across all yi values.

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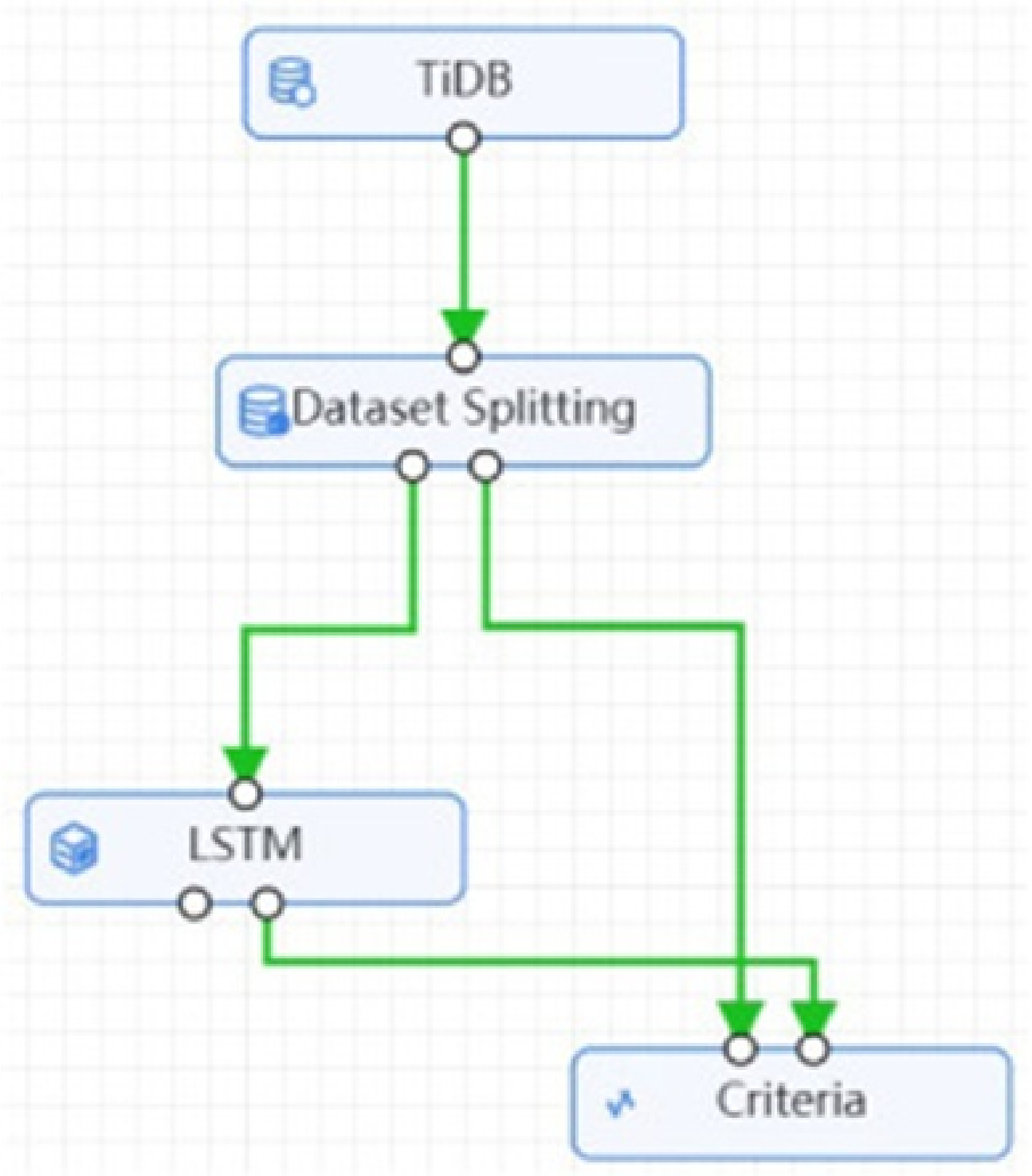

Figure 15. Workflow of the inflow forecast in X-AI.

As presented in **Figure 16**, the artifact logs an R^2 of 0.871 alongside a MAPE of 32.11% on the holdout partition. These numbers bear out the pipeline's prognostic potential, though extra accuracy polishing remains warranted to hit operational-grade thresholds.

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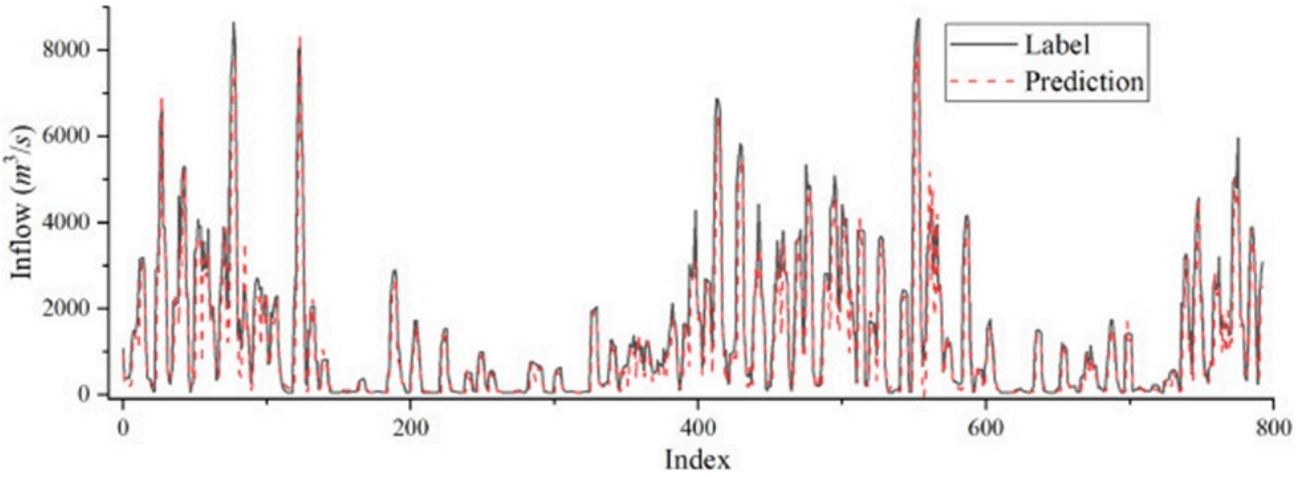

Figure 16. LSTM model performance.

Interactive model optimization via D2 and XGBoost

To further interrogate the agent faculties of X-AI, the identical problem is approached via XGBoost under the mentorship of the intelligent assistant D2.

Initial workflow and feedback loop

D2 initially proposes constructing an artifact that takes Station B outflow and daily precipitation as predictors. As shown in **Figure 17**, D2 pieces together the pipeline, activates an array of performance gauges (R^2, MAPE, MSE, RMSE, MAE, CV-RMSE), and registers that the starting R^2 (0.869), as collated in **Table 5**, proves wanting.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \quad (15)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \quad (16)$$

$$\mathrm{CV-RMSE} = \frac{\sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}}{\bar{y}} \quad (17)$$

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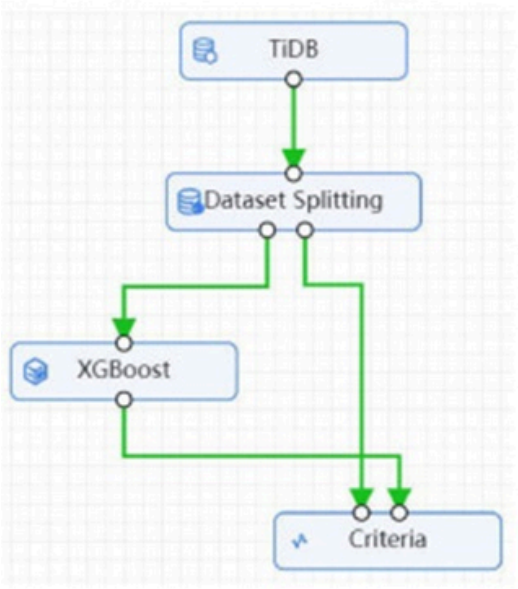
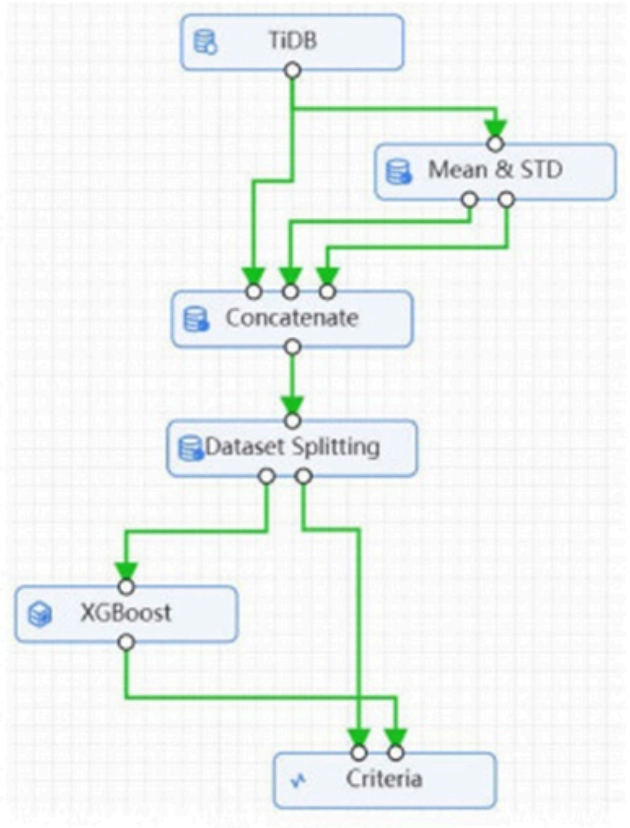
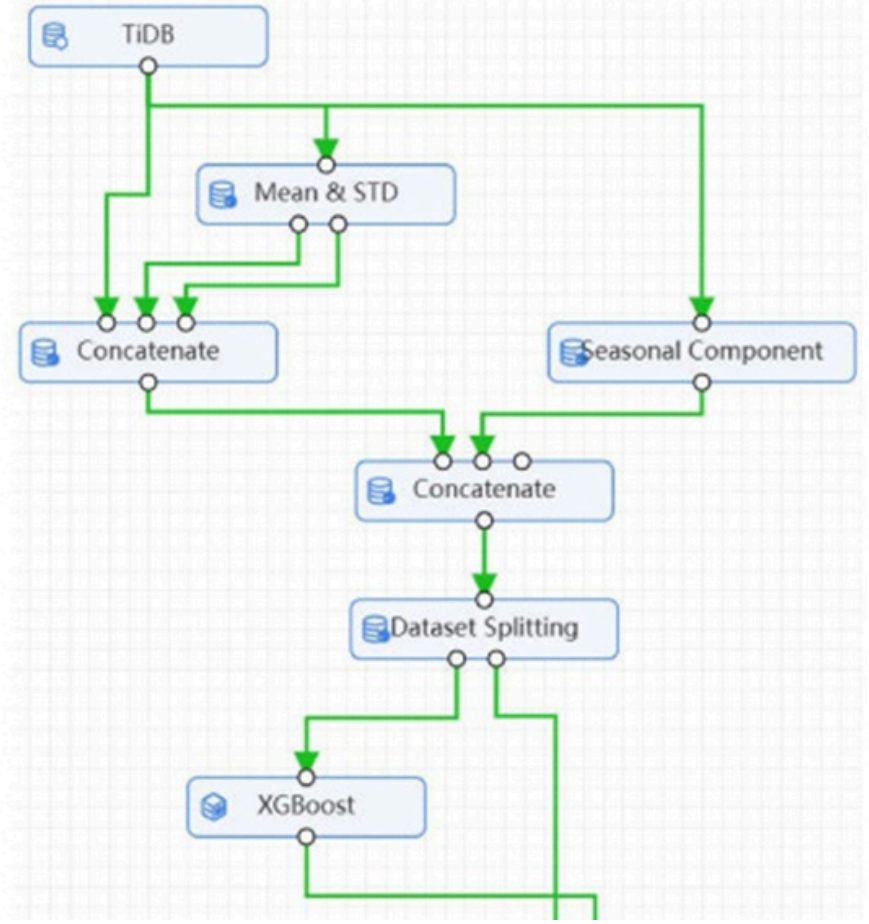


a. Chat 1



b. Chat 2



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c. Chats 3 & 4

Chat-1	0.221	187.582	35,187.033	143.105	0.869	0.180
Chat-2	0.197	162.901	27,305.041	118.996	0.889	0.137
Chat-3	0.183	155.331	24,127.734	107.87	0.910	0.129
Chat-4	0.181	153.141	23,452.224	103.778	0.922	0.127

Feature enhancement via periodicity analysis

During Chat 2, D2 proposes folding in yearly cyclic attributes, formulated as the mean and spread of inflow readings registered on the same calendar date over a multiyear archive.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} f_i, \sigma^2 = \frac{1}{N}\sum_{i}^{N}(f_i - \mu)^2 \quad (18)$$

Where μ denotes the average; σ2 denotes the spread; N denotes the count of records per calendar date; and f indicates the daily inflow measurement.

Figure 18 lays bare strong seasonal inflow rhythms. Pearson scrutiny, as rendered in **Figure 19**, substantiates significant year-to-year linkages, bearing out D2's design judgment. With the enriched predictor suite, R^2 ascends to 0.889.

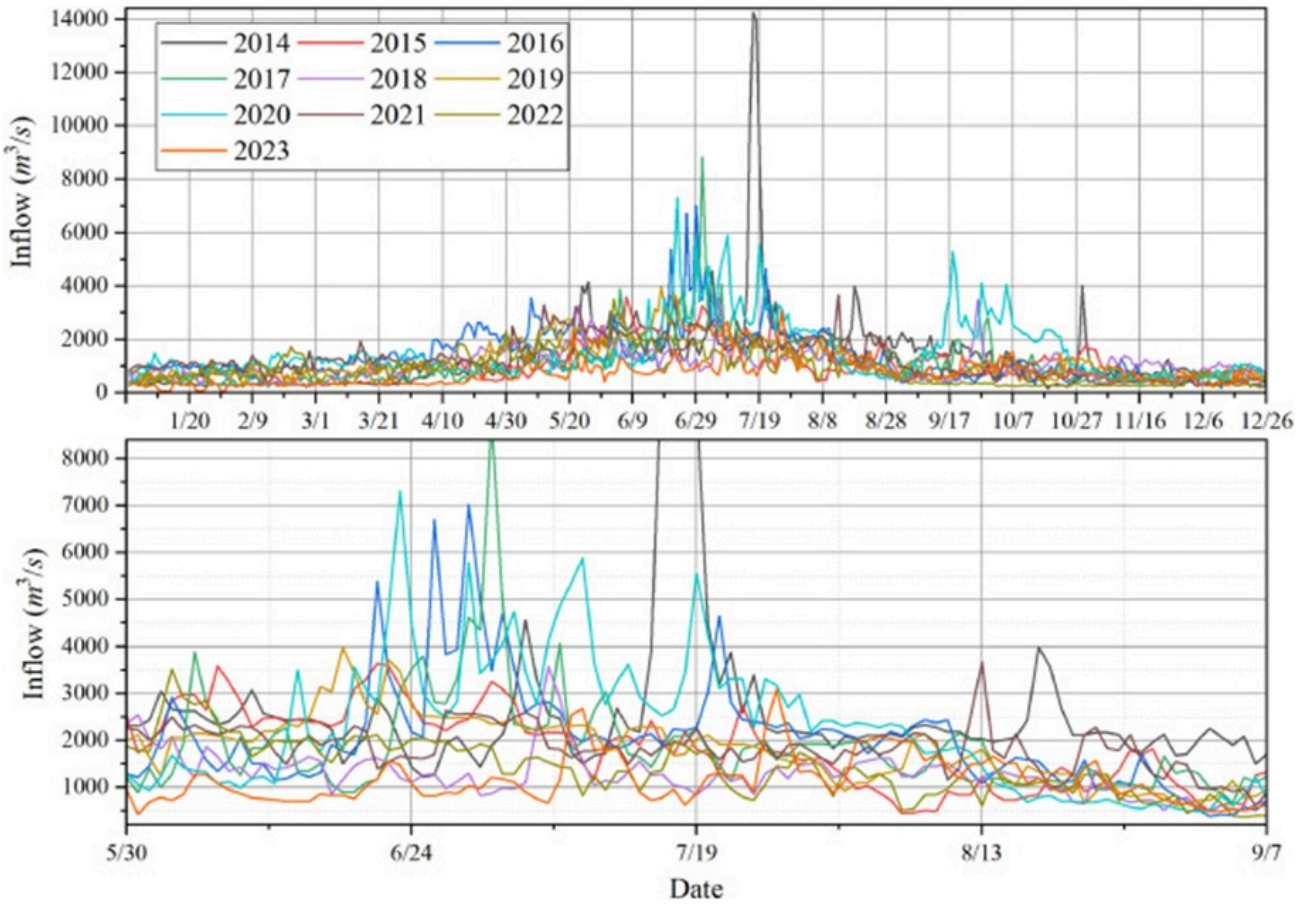

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Figure 18. Annual inflow distribution.

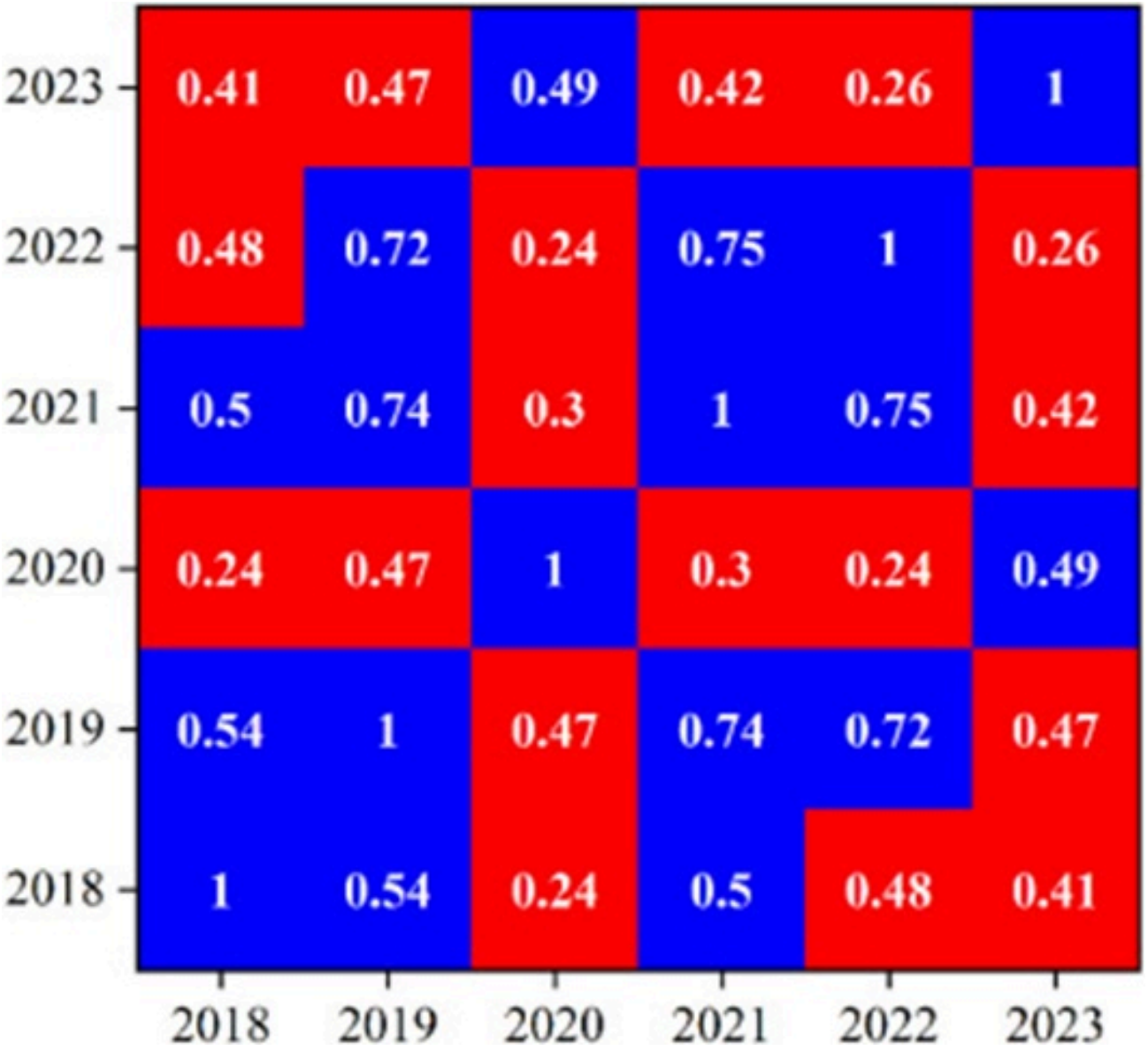

Figure 19. Correlation of inflow across years.

Seasonality modeling via additive decomposition

Within Chat 3, D2 invokes seasonal decomposition [56] via a 365-day rolling smoother with periodic leftover averaging. Additive decomposition disentangles a temporal series into trend, cyclical, and leftover constituents. For a temporal series Yt:

$$Y_t = T_t + S_t + R_t \quad (19)$$

Where Tt stands for the trend constituent at instant t (reflecting long-run movement); St stands for the cyclical constituent (recurrent motifs over fixed intervals); and Rt stands for the leftover constituent (erratic jolts not accounted for by trend and cyclical elements).

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The trend constituent gets teased out through a moving-average smoother applied to the temporal series.

$$T_t = \frac{1}{k} \sum_{i=-\frac{k-1}{2}}^{\frac{k-1}{2}} Y_{t+i} \quad (20)$$

Where k denotes the window extent, conventionally selected to match the cyclical interval—365 in this context.

For every cyclical position, the typical leftover across all periods gets derived. The cyclical constituent is computed as follows:

$$S_t = \frac{1}{N} \sum_{i=0}^{N-1} \left(Y_{t+ip} - T_{t+ip} \right) \quad (21)$$

Where p indicates the interval, and N indicates the tally of observations per cyclical position.

The leftover constituent is then isolated by peeling both trend and cyclical constituents away from the native temporal series.

$$R_t = Y_t - T_t - S_t \quad (22)$$

The cyclical constituent of inflow is worked out as exhibited in **Figure 20**. As mirrored in **Table 5**, the bump in R^2 confirms that D2's determination was well-founded. In the fourth round of dialogue (Chat 4), D2 relays that additional accuracy gains atop the present base may be pursued through hyperparameter manipulation. Simultaneously, D2 nudges the XGBoost learning rate downward from 0.1 to 0.01, netting marginal uplift, as collated in **Table 5**. The closing distributions of labeled versus projected readings are plotted in **Figure 21.**

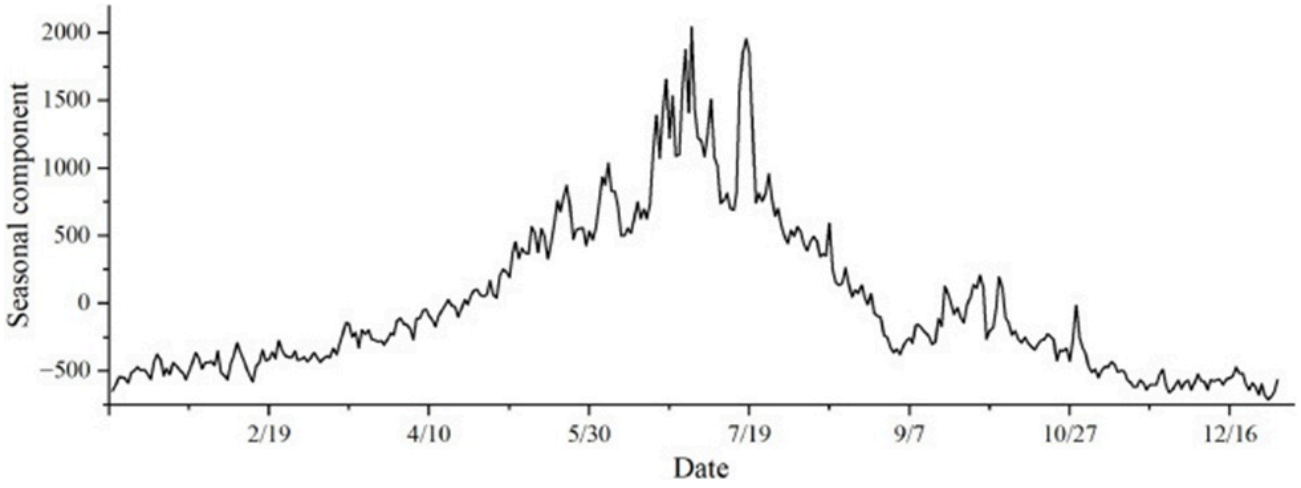

Figure 20. The seasonal component of the inflow.

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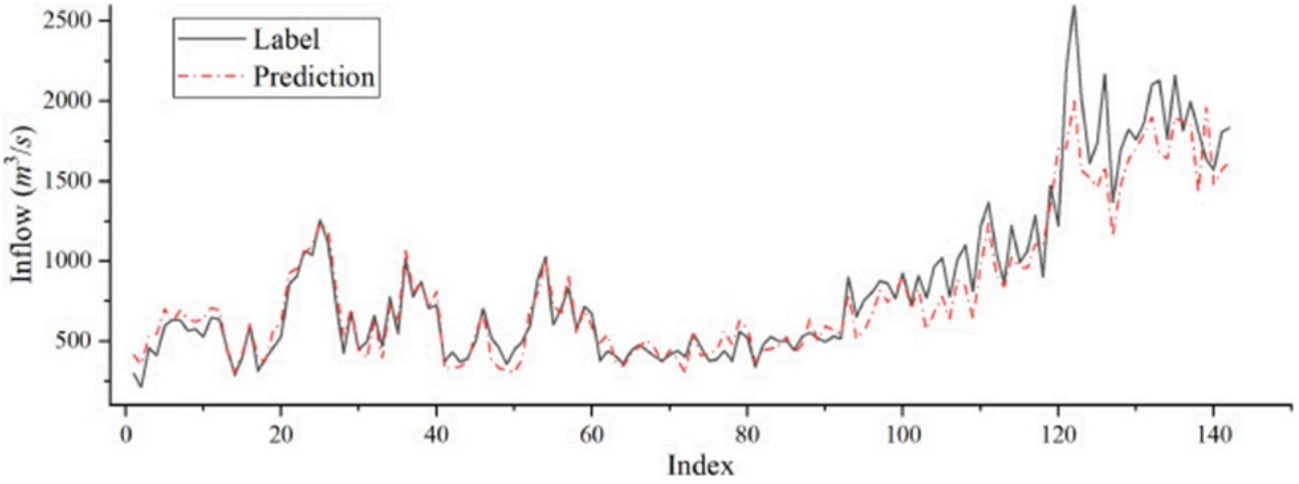

Figure 21. Testing results of the trained XGBoost.

Comparative analysis: LSTM vs. D2-Enhanced XGBoost

To measure the imprint of intelligent assistant scaffolding on modeling yield, we perform a head-to-head examination between two modeling paradigms realized inside X-AI: an LSTM-grounded temporal model and an XGBoost regression model refined under D2's guidance.

The LSTM artifact musters an R2 of 0.871 alongside a MAPE of 32.11% on the holdout set. While this showing lands within acceptable bounds, subsequent refinement is hemmed in by a static predictor roster and handcrafted tuning.

By comparison, the D2-steered modeling sequence registers appreciable advances. Through stepwise direction of predictor expansion, incorporation of periodicity appraisal, deployment of seasonal decomposition, and hyperparameter recalibration, D2 steers the XGBoost artifact toward an R2 of 0.889 and a slimmed MAPE of 29.64 %. Beyond that, the D2-mentored artifact surpasses LSTM on auxiliary standard gauges, notably MSE and RMSE, as depicted in **Figure 21.**

Transcending bare numeric exactness, D2 enriches the modeling journey along several cardinal axes:

• Compressed Iterative Modeling. By flagging performance chokepoints and proposing focused refinements (e.g., new predictors, architectural adjustments), D2 reduces the number of manual iterations required for convergence.

• Domain Knowledge Embedding. D2 encodes sector-specific sensibilities into predictor engineering playbooks, enabling energy practitioners to unearth latent motifs without exhaustive statistical dissection.

• Mental Load Abatement. Through natural language back-and-forth and self-acting tool orchestration, D2 reduces the technical barricade confronting non-AI operators, freeing domain specialists to center on judgment rather than implementation minutiae.

• Traceability and Intelligibility. D2's inferential footprints remain auditable, deepening operator confidence and pipeline interpretability.

In aggregate, the comparison spotlights the force of pairing strong base learners like XGBoost with intelligent assistant-led refinement. While LSTM stays capable for temporal modeling tasks, the blending of D2 showcases superior approachability, malleability, and prognostic punch.

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This instance verifies that the X-AI ecosystem, supercharged by D2, supports efficient, exacting, and operator-accessible fielding of AI artifacts within energy forecasting undertakings. The blueprint is extensible and transferable to other energy contexts, including load projection, malfunction isolation, and renewables integration planning.

Conclusion

This study recounts the conception, engineering, and substantiation of X-AI, an intelligent, pipeline-centric ecosystem architected to propel domain-adapted AI deployment throughout the energy landscape. X-AI spans the gulf between AI potential and domain practitioners by furnishing a code-absent, scalable, and interpretable modeling habitat, equipping non-AI specialists to independently conceive, field, and steward intelligent remedies for energy-tied assignments.

A cardinal breakthrough lies in the interweaving of LLMs, which lifts system cognition from mechanized algorithmic number-crunching to conversational inferencing. This shift markedly depresses the uptake barrier and rewires how operators engage with AI ecosystems. The embedded intelligent assistant, D2, operates as a cognitive collaborator, skilled at parsing natural language interrogations, fetching sector-specific intelligence, piecing together visual pipelines, and performing cyclical reasoning to elevate artifact exactness. Through such human-focused dialogue, elaborate undertakings like inflow projection and artifact calibration become realizable absent programming know-how.

To gauge the ecosystem's heft, an original usability metric, COER, is proposed, marrying task throughput with mental burden. Experimental outcomes reveal that D2 magnifies aggregate ecosystem usability by >8× relative to the baseline setup, supporting the system's capacity to trim modeling complexity and cognitive strain.

A case investigation into hydropower inflow projection demonstrates the pragmatic worth of X-AI. By juxtaposing a conventional LSTM artifact against a D2-mentored XGBoost pipeline, the examination reveals how intelligent assistant scaffolding can lift forecast accuracy through predictor augmentation, cyclic motif detection, and adaptive refinement. These revelations spotlight D2's merit not just as an aide but as an ingrained reasoning engine inside an expert-system scaffold.

This investigation delivers:

1. A modular and field-ready AI ecosystem purpose-tuned for intelligent energy system implementations;

2. An LLM-fueled agent scaffold that heightens usability through conversational back-and-forth and self-directed decision counsel;

3. A fresh appraisal gauge (COER) that bridges human-computer interplay and performance quantification;

4. A tangible energy forecasting demonstration evidencing system fusion, automation, and inferential muscle.

These revelations situate X-AI as a workable and stretchable expert system for intelligent energy modeling and decision support. Forthcoming pursuits will zero in on broadening the ecosystem to encompass live grid operations, renewable output projection, and multi-agent orchestration across distributed energy configurations.

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Conflict of interest

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None

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